Review of the Development and Application of Visual Sensors based on Event Streaming

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Abstract

Event-based vision sensors efficiently capture changes in motion in a scene in real time. Unlike traditional camera principles, event cameras only report pixel-level brightness changes with low latency, low redundancy, and high dynamic range. Therefore, cameras have been widely used in image processing, computer vision, state estimation and other research directions. This paper explains the basic principles and structure of event cameras, compares three typical event cameras, and analyzes their respective advantages and application scenarios. Secondly, this paper reviews the application of event cameras in the research directions of event stream noise reduction, feature extraction, object detection, depth estimation, visual SLAM, optical flow estimation and multi-sensor fusion, summarizes the advantages and disadvantages of event cameras, and evaluates and prospects its development prospects in different application scenarios. Finally, its future development trend is discussed.

Keywords: Event camera, High-speed target recognition, Event stream processing

1 Introduction

With the development of object detection technology, the requirements for camera performance in different fields are also increasing. A traditional camera is a frame-based vision sensor. The principle is to transmit all the information in the scene back at the same moment by presetting a certain exposure time. In practical applications, traditional cameras still have the following shortcomings. 1. The camera output is a fixed-time frame sequence, which cannot detect the change of the target in the adjacent image frame. This characteristic results in the loss of a lot of inter-frame information. The problem of information loss is particularly serious when detecting some high-speed moving objects [1]. 2. The traditional camera is to obtain all the information in the scene at a certain moment and then outputs the image. When studying the moving object, we only focus on the moving object. Repeated feedback of the entire image information will cause a large amount of background information redundancy and become a burden of information processing [1]. 3. The traditional camera adopts synchronous exposure technology to record the light intensity information of each pixel in the scene. When facing a scene with too high or too low light intensity, the traditional camera will be overexposed or underexposed due to the characteristics of directly obtaining the absolute value of the light intensity. Therefore, it will not be able to reflect the information of the target object well [1].

Faced with the shortcomings of traditional cameras in the above situations, people wanted to invent a new camera to meet the needs of special scenarios. In the early 20th century, researchers found through biological vision that the way the human eye obtains information is different from the synchronous recording and transmission of data by traditional cameras. The human eye obtains scene information and asynchronously transmits it back to the brain [2] and it pays more attention to the moving objects in the picture. Based on such biological phenomena, researchers invent an event-based vision sensor. This event-based vision sensor independently detects changes in light intensity per pixel and records and compares them logarithmically, and this dynamic vision sensor can accomplish some tasks that standard frame-based cameras cannot do, such as high-speed motion estimation, high dynamic range mapping, and so on. Event cameras are rapidly developing in various fields, including embedded event cameras (eDVS), inertial event cameras DAVIS240 [3], high-speed event cameras using the G-AER protocol DVS-Gen [4], optical flow event cameras CeleX-4/5 [5-6], color event cameras SDAVIS192 and ColorDAVIS346 [7-8], and superspeed full-event cameras that mimic the fovea of the retina SpikeOne [9] and others. The new event camera is constantly improving its working performance and improving the application scenarios. The new event camera can more fully simulate the effect of the biological retina in the foreseeable future.

This paper first explains the basic principle and structure of event cameras, and compares the application scenarios of different event cameras. Secondly, this paper introduces the development and application of event cameras in various research directions such as event stream noise reduction, feature extraction, and object detection. Finally, the future development trend of event cameras is discussed.

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2 Introduction to Event Camera

2.1 Event Camera Overview

In the traditional field of vision, cameras use the method of synchronous transmission of information. At a certain moment, the camera makes exposure and transmits information from all pixels at that moment at the same time. All pixel information on the image is generated at the same time. The event camera mimics some characteristics of the human retina, and its shooting idea is completely different from that of standard cameras.

Event cameras are also known as silicon retinas. In the early 90s, Mahowald et al [10]. developed the first silicon retina, which was the earliest form of event camera. In the subsequent research process, researchers continue to add other sensors on this basis, so that their functions are constantly improved and expanded. In 2008, as Delbruck et al. [11] proposed the event camera of the dynamic vision sensor (DVS). It marks that the event camera officially entered the process of commercialization.

In the entire area that the event camera can detect, as long as a one-pixel brightness change exceeds the set threshold, a message will be transmitted back. The information it sends back is called an event, and the format of an event is a four-dimensional vector, e = (x, y, t, p). (x, y) reflects the coordinates of the location of the change in light intensity, t represents the time of the event, and p represents the polarity information of whether the pixel becomes lighter or darker. Each event carries a timestamp. All events occur asynchronously because even the smallest time intervals are impossible to be completely simultaneous. The light intensity of pixel x_k at t_k time is expressed logarithmically as [12]:

$$L(x_k, t_k) = \log(x_k, t_k) \quad \textbf{(1)}$$

It is specified that the difference between the logarithmic change of light intensity that occurs at the time of t_k and the logarithm of light intensity at the time of the previous excitation event exceeds the preset threshold, that is [2]:

$$\Delta L(\mathrm{x_k}, t_k) = P_k C \quad \textbf{(2)}$$

$$\Delta L(x_k, t_k) = L(x_k, t_k) - L(x_k, t_k - \Delta t_k) \quad \textbf{(3)}$$

At this time, the event e_k is fired. All pixels in the sensor simultaneously perform asynchronous light intensity detection and output event information, forming an asynchronous event stream.

As shown in Figure 1, different events are output at each moment. The red dot indicates that the pixel is brightened and the blue dot indicates that the pixel is darkened.

With the continuous improvement of event-based algorithms, event cameras are gradually becoming commercialized. The most typical event cameras are DVS [13], asynchronous time based image sensor (ATIS) [14], and dynamic and active pixel vision sensor (DAVIS).

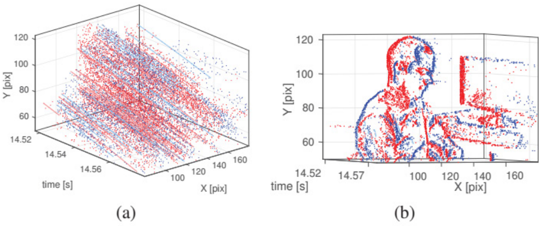

Figure 1. Schematic diagram of event flow [2]

2.2 DVS

Dynamic Vision Sensor. It is the first and most basic event camera. DVS simulates the characteristics of biological retinal spatial vision. It is committed to detecting dynamic information in the scene, and can complete the most basic functions of event cameras. Each pixel of it detects changes in light intensity independently and compares them logarithmically. Output an asynchronous event when the amount of change reaches the set value. However, DVS can only output event information, not grayscale information, so its visibility is poor. The circuit structure of DVS is shown in Figure 2. It consists of a differential circuit, logarithmic photoreceptors and two comparators.

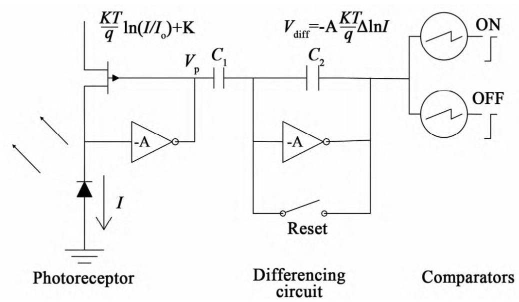

Figure 2. DVS circuit structure [12]

2.3 ATIS

Image sensors based on asynchronous events were proposed in 2008. The above DVS only transmits the address, time, and polarity of the pixel, and does not output environmental grayscale information. Therefore, it cannot meet the needs of visualization. Based on obtaining event information, the requirements of visualization [12] were also met, and ATIS came into being. The ATIS circuit structure is shown in the Figure 3 and Figure 4. It contains a change detector and a photometric device. The change detector section contains the complete DVS pixel structure. It can detect changes in light intensity and output asynchronous event streams, which is responsible for completing the event stream acquisition of the camera.

The photoreceptor of the photometric device detects changes in light intensity and exposes it. The exposure method of ATIS light measurement equipment is different from that of conventional cameras. The exposure method of traditional cameras is generally global exposure. It adopts the method of presetting the exposure time and determines the gray value of the pixel by measuring the voltage across the capacitor after exposure, and there is a mechanical limit for the minimum exposure time. The optical measurement section of ATIS resets a capacitor to a high level when the change detector detects a change in light intensity for event transmission. As the time of exposure to light increases, the voltage across the capacitor drops. The voltage drop time across the capacitor determines the gray value of the pixel. Although ATIS has a certain degree of visibility, because of its time-based exposure method, it is prone to abnormal exposure when the ambient brightness does not change significantly.

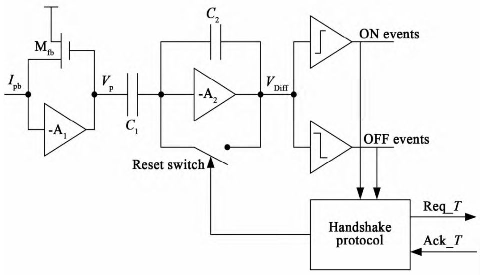

Figure 3. ATIS change detector circuit structure [12]

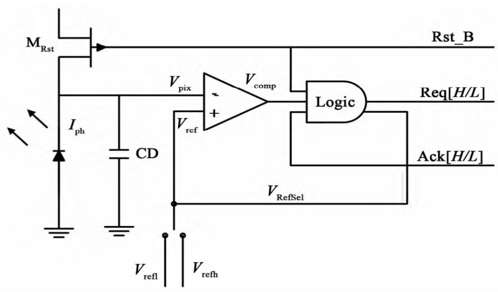

Figure 4. Circuit structure of ATIS optical measurement part [12]

2.4 DAVIS

Although DVS has been successfully used in computer vision tasks, it is difficult to recover its video compression signal. ATIS allows overcoming this problem by providing access to absolute light intensity, but there is a problem with motion artifacts. In 2014, Brandli et al. [15] developed a new event camera called DAVIS. The structure of DAVIS is shown in Figure 5. It is divided into two parts: APS (Active pixel sensor) and DVS. DVS is responsible for detecting changes in light intensity and outputting asynchronous event stream information, and APS performs synchronous exposure to obtain the grayscale information of the scene. The grayscale image obtained by APS does not have the problem of abnormal exposure and information loss of APIS. Because it adopts the synchronous exposure method. In fact, DAVIS is a combination of event cameras and traditional cameras. As a result, it is temporally and spatially redundant, and the APS cannot adapt to high dynamic range environments like event cameras. Therefore, DAVIS is suitable for applications where visualization is critical.

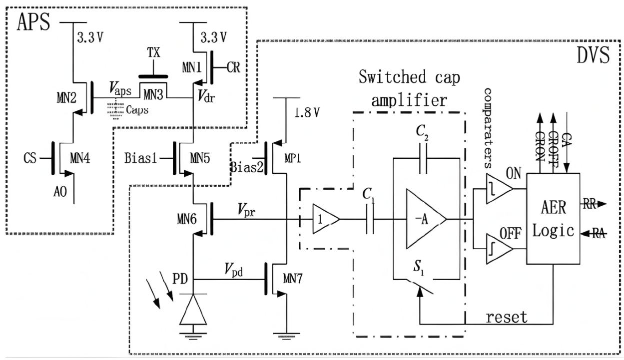

Figure 5. DAVIS circuit structure diagram [2]

According to the differences in performance and principle, the characteristics and use cases of these three cameras are listed in the Table 1.

Table 1. DVS, APIS, DAVIS comparison table [12]

Types	Features	Usage
DVS	It is the most basic event camera, which can complete the output of the event stream and has the characteristics of high dynamic range and low latency, but low visibility.	It is generally used to detect high-speed moving objects and has low visualization requirements.
ATIS	It can obtain grayscale information and has good visibility, but due to its time-based exposure method, it is easy to lead to exposure failure and information loss	It is suitable for scenes with frequent changes in scene brightness and high-speed motion.
DAVIS	It can output environmental event information and grayscale information and has good visibility, but its part is composed of APS. It is limited by the shortcomings of traditional cameras.	It is used in scenarios that require high visibility, such as target identification, tracking, and positioning.

3 Pros and Cons of Event Camera

This section discusses the advantages, shortcomings and application scenarios of event cameras. He has the advantages of high dynamic range, low latency to reduce data and bandwidth, but also suffers from incompatibility with traditional algorithms, the need for noise processing, and the large amount of output data. Overall, event cameras offer significant advantages in terms of dynamic range and speed, but need to be offer significant advantages, but new processing techniques are needed to fully utilize their potential and manage their data output. This paper will analyze the strengths and weaknesses of event cameras in detail.

3.1 Advantages

1) High dynamic range. The event camera detects the change of the object by outputting the event according to the brightness change and is not sensitive to the absolute brightness of the image. The brightness detection of its pixels is logarithmic.

Therefore, in scenes with large or small light intensity, traditional cameras cannot represent the target object well, while event cameras are not affected [1].

2) Low latency. Compared with the frame-based image acquisition method of standard cameras, the brightness change of event camera captures without exposure time limitation [12], and real-time feedback can be achieved for the motion change of the target. Event cameras can generate event information in sub-millisecond times. This high-speed feature makes it suitable for high-speed motion applications. Event cameras cost less and have more computing power than conventional cameras capable of achieving the same frame rate. Figure 6 shows a comparison of the display results of a standard camera and an event camera in a high-speed motion scene. From the figure, we can clearly see that when the object moves rapidly, the output of the event camera can more clearly express the movement trajectory.

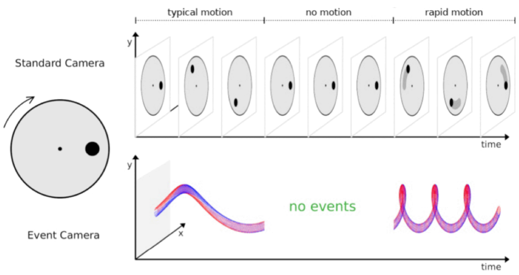

Figure 6. Comparison between event camera and traditional camera [16]

3) Small amount of data, low bandwidth. The output form of an event camera is a vector that represents information about the change in brightness of image pixels. The entire image information is not transmitted back, which greatly reduces data redundancy and transmission bandwidth occupation. If the objects in the scene do not move and the light source does not change, asynchronous events will not be output, and the transmission bandwidth will not be occupied. In addition, frame-based pre-processing operations in standard cameras are no longer required in event-based processing, so algorithms enable faster responses, which is especially beneficial for embedded real-time systems.

3.2 Shortcoming

1) Event streams cannot be used directly by traditional algorithms. Before the advent of event cameras, traditional object detection algorithms were used to detect frame images recorded by standard cameras. The event stream output by the event camera cannot be directly detected by traditional machine vision algorithms, so a paradigm shift is required [1]. At present, some researchers use the method of cumulative events to change the event stream into event frames, and then use traditional algorithms to detect them. In 2020, Chen's team proposed a method for luminance image reconstruction [17]. The model is trained on the simulated event dataset, and the perceived loss of the generated image is gradually reduced through training, so that the generated image gradually approaches the target image. In 2022, Kun Xiao's team proposed a new method for accumulating pseudo-image frames from event cameras called time slicing and digital slicing [18]. Figure 7 shows a schematic of this method. This method can output event frames of the same window size at the same time interval, which is compatible with traditional SLAM systems and reflects scene information well.

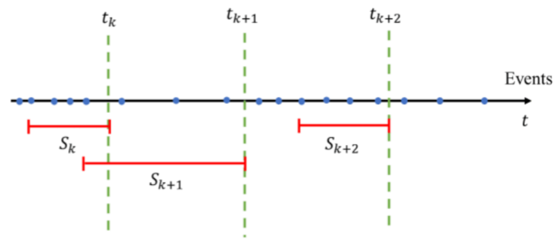

Figure 7. Schematic diagram of time slices and digital slices [18]

However, this processing method still uses the traditional image frame method, does not take advantage of the asynchronous nature of the event stream, and abandons the high-speed advantage of the event camera. Therefore, scholars should design an event processing algorithm that integrates asynchronous event streams to bring out the rapidity of event cameras.

The Figure 8 shows the pseudo-image frame obtained through the cumulative event. When the sampling interval is set to be small, less information about the brightness change is obtained, so the outline in the image is blurred. When the time interval is large, the scene outline is obvious, but there may be information redundancy.

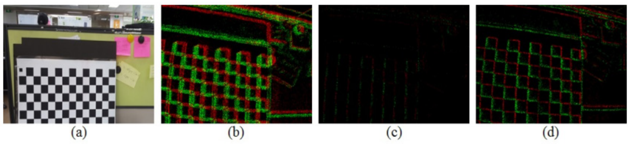

Figure 8. (a) to (d) Fixed time accumulated event frame

In 2019, Scheerlinck's team [19] proposed a method for calculating the convolution of linear spatial kernels with event camera outputs. This method differs from the current method of synthesizing pseudo-image frames through cumulative events but operates directly on asynchronous event streams. The core of this method is to introduce the internal state of directly encoded convolutional image information, which is updated asynchronously when each event arrives from the camera. The state information is read at any time. Through real-time asynchronous updates, it is synchronized with changes in event information for use by other vision algorithms in real-time robot systems.

2) Existence of noise. Due to its sensitivity to brightness changes, event cameras still have the problem of noise interference in practical applications. The structure of the event camera is to detect changes in the ambient brightness, so some background changes in the environment will also cause the camera to output event streams, and there are many environmental noise interferences in the output event streams. Increasing the threshold of the camera to detect light intensity changes will help reduce noise. But at the same time, the collection of information on pixel light intensity changes caused by object movement will also be reduced, which will lead to information loss. Therefore, denoising the event stream is a very important preprocessing link. In 2008 Delbruck et al. [20] proposed a noise-filtering method based on the temporal and spatial correlation of events. This method records the time when the target event occurs and compares it with the events that occurred within the set time in its spatial domain. If the interval between two events exceeds the set time, it will be identified as noise and filtered. This noise reduction method takes advantage of the spatial and temporal continuity of moving objects. It can effectively reduce the interference of background noise. In 2019, Fairouz et al. [21] compared the trigger conditions of event transmission between the actual system and the virtual reference system and constructed an online estimator to derive the interference value. But this method needs to check the event trigger condition at each time point and is not a self-triggering scheme. In 2020, Changda Yen et al. and others proposed a noise processing method based on time-space continuity [22]. Events occur continuously in space and time, while noise occurs randomly. Therefore, when you want to process an image at a certain time, you only need to consider whether there are related events in the spatial field before and after the event to determine whether the event is noise. Figure 9 is a comparison of the effects of using the noise reduction method proposed by Changda Yan's team.

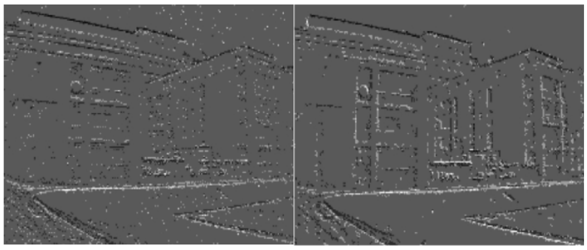

Figure 9. Output comparison before and after denoising [22]

In 2023, Xiaoli Zhou's team proposed a spatial target event stream noise reduction algorithm [23]. Aiming at the noise processing problem of event stream data of spatial targets, they perform local spatial noise reduction processing on each time domain on the classical spatiotemporal filter. At the same time, cascaded filters for NDSEF (Neighborhood Density-based Spatiotemporal Event Filter) are proposed for different scenarios and targets. Both the classical filter and the NDSEF algorithm are single-stage filters with limited noise reduction effects for spatial event streams. The cascade filter algorithm gradually refines the event data by increasing the accumulation window of the pixel dimension, ensuring the filtering speed of the algorithm, retaining the originality of the target event, and improving the signal-to-noise ratio. Figure 10 compares the noise reduction results of the classic filter, NDSEF filter, and cascade filter.

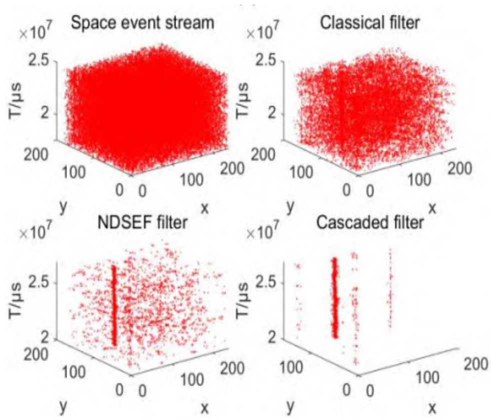

Figure 10. A comparison chart of three noise reduction methods [23]

It can be seen from the above figure that the NDSEF algorithm can effectively reduce noise interference compared with classical filters, but there are still some interferences that have not been removed. The cascaded filter performance is the best.

3) The data volume of event cameras is huge. When detecting high-speed moving objects, the event vector output by the event camera per second is very large. Although this can make it well represent the motion changes of the scene, it also puts pressure on data processing. In 2022, Rosa et al. proposed a high-throughput asynchronous convolution method based on

event cameras for this situation. This method can achieve processing more than 10 million events per second [24].

4 Current Application Direction

Due to some problems with the event camera itself, researchers are constantly optimizing. Event cameras can replace traditional cameras in some applications, such as high-speed motion estimation, high dynamic range mapping, and so on. Because of its good performance compared to traditional cameras, it is currently used in many fields of traditional cameras. Such as feature detection and tracking, optical flow estimation, 3D reconstruction, and attitude estimation. At the same time, because the event stream output by the event camera cannot be directly used by traditional object detection algorithms, researchers are also developing event-based direct detection methods. Next, the current application direction and research progress of event cameras are introduced.

4.1 Event-Based Feature Extraction

In traditional computer vision algorithms, feature detection is an important image processing method, mainly including corner point detection, edge detection, and so on. These image processing methods are to identify and intercept the representative features in the image to characterize the entire image. These methods can greatly reduce the information redundancy during image processing and improve the work efficiency of the object detection algorithm. These local features represent the overall image method is widely used in image retrieval, action, and object recognition, texture classification and other scenarios.

In the face of high-speed motion scenes, event-based feature extraction methods can detect faster and more effectively than traditional frame-based feature detection. The researchers propose a variety of feature detection and tracking methods based on event cameras, and the detection and tracking features can be roughly divided into corner point features, features based on three-dimensional event point cloud distribution, and features based on motion/optical flow distribution.

Traditional corner extraction feature extractors are generally based on manual design. Because of the characteristics of asynchronous event streams, it is necessary to design a new corner extraction method. In 2019, C. Scheerlinck et al. [19] proposed a method for calculating the convolution of linear space kernels and event camera outputs. This method does not need to accumulate event streams to generate pseudo-image frames and directly operates on asynchronous event streams. In the same year, Li's team [25] proposed a novel corner detection method based on fast asynchronous events, called FA-Harris. The proposed G-SAE maintenance algorithm and corner candidate algorithm greatly improve the real-time detection of corner spots. In 2020, Hochang Seok's team proposed a robust feature tracking method for DVS event streams based on B'ezier mapping [26]. They employ a method of aligning events along the B-curve over time intervals to minimize misalignment. Extensive experimental evaluation in 2D feature tracking and 3D pose estimation shows that this method is significantly superior to traditional methods. In 2022, Xinghua Liu et al. [27] proposed the frame-based feature extraction and EKF framework of event cameras [28], and developed a low-latency, event-based visual mileage calculation method. This algorithm detects features and tracks motion on the image plane, and then tightly interweaves feature-based pose estimation and Extended Kalman Filter (EKF) frameworks in event-based visual odometry to obtain low-latency and high-rate tracked trajectories.

Overall, these advances show that event-based feature extraction and tracking methods are more effective than traditional methods when dealing with fast and dynamic scenes, opening up new directions for future research in image processing and machine vision.

4.2 Event-Based Object Detection

Object detection is the task of extracting target objects from a complex scene and identifying and tracking them. Traditional cameras are frame-based, isometric sampling, which inevitably leads to the loss of object motion information between frames. So traditional cameras perform poorly when tracking high-speed moving objects. At the same time, at the sampling moment, the image of each frame repeatedly records the background information in the scene, resulting in a great degree of redundancy in image processing. The event camera only reports the part of the light intensity change, ignoring the background information. So it performs well in the detection and tracking of high-speed moving objects.

Lizenberger et al. proposed a target tracking algorithm based on monocular DVS in 2006 [29], which was inspired by the mean shift method to realize continuous clustering of address events and cluster tracking. They use data from asynchronous transient vision sensors to monitor and track traffic scenarios. Drazen et al. proposed a new camera technology for particle tracking velocimetry (PTV) in 2011 [30]. The technology consists of dynamic vision sensors (DVS) that work in parallel with pixels, comparing the tracking capabilities of DVS to CMOS cameras. In 2018, Akolkar et al. proposed a novel visual flow algorithm based on multi-scale plane fitting [31], and the calculation speed is fast and efficient. In 2021, Pengju Li et al. [32] applied event cameras to the design of monitoring systems to achieve the purpose of working in a large brightness range. In 2022, Gava et al. [33] combined ATIS cameras with PUCK tracking algorithms to apply visual tracking tasks for ice hockey.

Overall, these current research advances show the advantages of event cameras for high-speed moving object detection and tracking, enabling effective applications in a variety of complex dynamic scenes by ignoring background information and focusing on light intensity changes.

4.3 Event-Based Depth Estimation

Real-world depth-sensing applications require precise responses to the rapid movement of a target. Depth calculation methods based on standard CMOS cameras [34], such as stereo matching, cannot be guaranteed in the case of noise or void depth inaccuracy. The event camera DVS (Dynamic Vision Sensor) is designed to achieve robustness to fast motion and light changes in a low-power and sparse representation. It has better performance than standard cameras in the field of depth perception.

Depth estimation refers to the problem of extrapolating the distance from the vision sensor to an object in the scene. Due to the close connection with the human binocular system, most of the current related work uses binocular event cameras for depth estimation. Traditional CMOS cameras have problems such as motion blur in the face of high-speed motion and high dynamic range scenes. Therefore, it is necessary to apply a new event-based depth perception method to the above scenarios. Although event-based sensors have good speed, their sparse representation and asynchronous output cannot be directly used in traditional stereo matching and depth estimation frameworks. New algorithms are needed to process this data.

Firouzi proposed an event-based parallax matching algorithm in 2016 [35]. This method uses dynamic collaborative neural networks for reliable 3D depth perception. One of the important methods for calculating depth by stereoscopic matching depth. Zou et al. [36] proposed in 2017 a method for event stream augmentation and estimation of density depth through event-driven stereo matching. They propose an event feature descriptor that is invariant to the translation, scale, and rotation of the event map. This event feature is conducive to DVS stereo matching and stereoscopic DVS generation of dense depth maps. In 2023, Sankeerth Durvasula's team proposed a new EV-conv method [37]. This approach speeds up CNNs for tasks such as depth estimation, object recognition, and optical flow estimation by a factor of 1.6 with little loss of accuracy.

The above studies have shown that event-based sensors and algorithms are more efficient and robust than traditional CMOS camera approaches when dealing with depth perception problems in high-speed dynamic scenes and high-dynamic-range scenes, but new algorithmic frameworks are needed to deal with these event streaming data.

4.4 Event-Based Visual SALM

Vision SLAM using standard cameras is prone to failure in scenarios such as motion blur and high dynamic range. While the low latency and insensitivity to the absolute light intensity of event cameras can improve the robustness of vision SLAM systems. As a result, event-based visual SLAM began to evolve gradually.

In 2013, Hoffmann et al. [38] conducted an autonomous indoor exploration of robots using an event-based vision SLAM system. They used an embedded event camera (eDVS) to provide pre-processed visual features of indoor ceilings for simultaneous positioning and mapping in real time. This positioning method uses the characteristics of the ceiling to accurately locate the position of the object in the room, but it cannot visually obtain information about obstacles on the floor. Therefore, a physical collision sensor is installed in the front of the robot to store the position of obstacles on the ground based on the bump information. The combination of the two sensors makes the autonomous exploration of robots possible. Figure 11 is a schematic diagram of indoor map construction using eDVS.

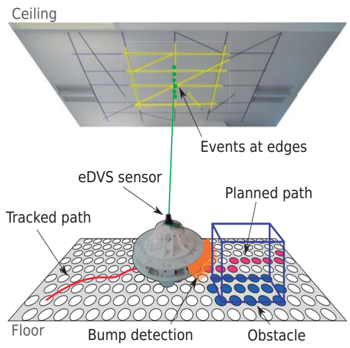

Figure 11. Indoor map building using eDVS [1]

In 2014, Weikersdorfer et al. [39] proposed an event-based 3D sensor combination and an event-based full 3D localization and mapping algorithm. He fused event cameras with RGB-D sensors to produce sparse 3D point streams. Because event-based sparse point streams generate fewer data, they are used efficiently. Moreover, their SLAM algorithms run 20 times faster than in real time.

In many related studies of event-based synchronous localization and mapping, solutions for module alignment and dense reconstruction have been proposed instead of directly extracting features from images. However, these methods are computationally expensive and cannot be applied to common robot platforms. Based on this status, in 2022, Chamorro et al. proposed a real-time PTAM fast-tracking algorithm [40], which greatly reduces the error of event line reprojection and realizes high-rate accurate camera pose estimation. Compared to EVO, its throughput is increased by 10-15 times, while also reducing computing costs.

Since different event accumulator settings led to different cumulative results, Kun Xiao's team researched how to accumulate event frames to achieve better event-based SLAM performance [18]. Through the analysis and adjustment of the slicing method, motion-free processing method, the use of polarity and the attenuation function, and verified on the dataset, the results show that the method has improved on different sequences.

This subsection discusses event-based vision SLAM techniques and their development. Overall, the current state of research demonstrates the effectiveness and advancement of event-based vision SLAM techniques in dealing with high-speed dynamics and complex lighting conditions, providing new possibilities for navigation and mapping of robots and autonomous systems.

4.5 Event-Based Optical Flow Estimation

Traditional optical flow estimation refers to the problem of calculating the speed of the target motion on the pixel plane without prior information about scene geometry or camera motion. Due to the camera's low temporal resolution, it is difficult for traditional optical cameras to continuously capture the rapid change of the position of objects in the imaging plane in high-speed motion scenes, resulting in motion blur in the output image frame. [38] The low frame rate data output by conventional cameras makes optical flow estimation algorithms inefficient for continuous optical flow estimation. However, event-based optical flow estimation is attractive. Event information containing timestamps can measure high-speed optical flow at low cost, so there is great promise for applying event cameras to optical flow estimation. Figure 12 records the display of a standard camera and an event camera facing a checkerboard with high-speed motion.

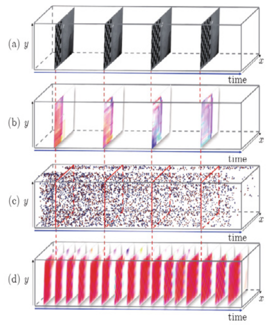

Figure 12. Comparison of optical flow estimation between traditional cameras and event cameras [38]

At present, the optical flow estimation algorithm based on an event camera is mainly divided into two types, purely based event stream and joint event stream and luminance image. The optical flow estimation algorithm [41] based solely on event flow can only reflect the optical flow information of the trigger position of the event point, and cannot obtain complete scene motion information, so there is a problem of insufficient spatial information. By studying the relationship between the blurred image frame and the event points generated during the exposure time, the continuous clear luminance image is reconstructed, and a smoothing constraint is added to the optical flow calculation to obtain a more robust dense optical flow, and finally, the continuous optical flow estimation is less affected by motion blur in high-speed motion scenes.

In 2017, Alex Junho Lee's team came up with event-based real-time optical flow estimation [42]. They proposed an algorithm to extract features and estimate their optical flow using only the event stream. In the same year, Jingyi Fu et al. derived a continuous sparse optical flow estimation method based on the joint EDI model [43] and the "constant brightness" assumption. It adds two smoothing constraint methods, HS [44] and CLG [45], to obtain a continuous dense optical flow field with robustness to noise. Assuming that the luminance image of frame i is Y[i] and the exposure time is T, the image generation model can be expressed as Equation (4)

$$Y[i] = \frac{1}{T}\int_{t}^{t+T} I(t)dt \tag{4}$$

Equation (5) establishes a connection between the blurred image, the instantaneous brightness image, and the incident. Since the blurred image and the event point are known, the instantaneous clear brightness image at any moment can be calculated by this formula.

$$Y(\mathrm{i}) = I(f) \bullet E_i(f) \tag{5}$$

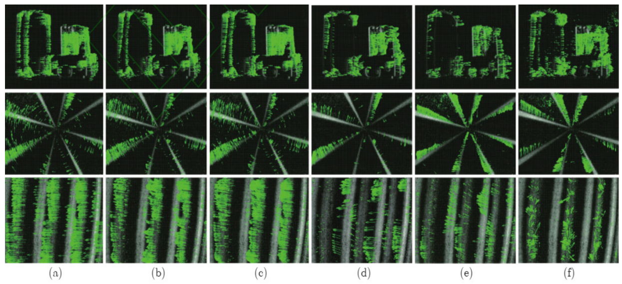

Figure 13. Comparison of the effects of different optical flow estimation algorithms [38]

Figure 13 shows the optical flow results obtained by different optical flow algorithms in the DAVIS240 dataset, where Figure 13(a) is the true value of optical flow. Figure 13(b) and Figure 13(c) show the results obtained by smoothing the constraint methods using HS and CLG. Figure 13(d) to Figure 13(f) are the results obtained by traditional methods, DAVIS-OF, DVS-CM, and DVS-LP. The optical flow estimation results obtained by using the EDI model are more in line with the actual true value of optical flow. The optical flow obtained by traditional methods has problems with motion blur and information loss.

This paper discusses the differences between traditional optical flow estimation and event-based camera optical flow estimation. In contrast, event-based optical flow estimation shows great promise for applications due to its ability to measure high-speed optical flows at low cost by including time-stamped event information.

4.6 Multi-Sensor Fusion

With the continuous development of event cameras, many new types of event cameras combine with other visual sensors based on ordinary event cameras. The inertial measurement unit (IMU), an internal receptor, is considered to be an effective supplement to visual receptors. So there have been more research results in recent years.

Zhu et al. extended the EM-ICP algorithm in 2017 [46] and proposed the first visual inertial mileage calculation method that combines characteristic events with IMUs, called EVIO. In this method, the camera pose estimation is completed by extracting the movement trajectory of feature points in the image from the event stream and fusing the trajectory with the measurement data of the IMU using the filtering method.

The accuracy of positioning and mapping of SLAM systems using filtering methods decreases rapidly due to the accumulation of errors caused by the linearization process. To face this problem, Rebecq et al. proposed a closely coupled visual inertial mileage calculation normal flow based on nonlinear optimization in 2017 [47]. This method select an event window with a fixed number of events to synthesize the event frame and compensate for the event stream based on the relative motion of the camera. Unlike the EVIO algorithm, this work uses keyframe-based nonlinear optimization techniques instead of filtering techniques in EVIO. In 2018, Rebecq et al. first proposed a state estimation method that tightly fuses event streams, standard image frames, and IMU measurement data. This method extracts the feature points in the event frame from the event camera and the image frame from the standard camera at the same time. Then it tracks the feature points and takes the tracking results of both as input of the nonlinear optimization method to complete the estimation of the camera pose. This method has higher accuracy, which is 130% higher than the method based only on event frames and IMUs, and 85% higher than the method based only on standard image frames and IMUs.

The main research directions are event streaming, image frame, and IMU fusion. Of course, a better solution is to integrate the IMU directly into the event camera, eliminating the tedious time synchronization. For example, based on DAVIS, the visual inertial odometer based on event cameras proposed by Mueggler et al. in 2018 [48] provides a method for directly fusing image frames, event streams, and IMU measurement data into VIO using continuous time frames. In 2020, Jung et al. [49] proposed an image, event stream, and IMU fusion pose estimation method based on constrained filtering to directly model the optical flow of event estimation, and the proposed algorithm reduced the position error by an average of 49.9%.

Overall, current research advances demonstrate the potential of event camera fusion with other sensors, such as IMUs, to improve accuracy and performance, especially in the areas of visual inertial mileage computation and state estimation in complex dynamic environments.

5 Conclusions and Potential Developments

This paper introduces the working principle, development process, and current application direction of the event camera. At present, due to its excellent characteristics, many researchers have tried to apply it in various machine vision fields.

Although the event camera has a good performance in many fields, there are still many problems. On the issue of the event camera itself, due to its special output format, traditional models cannot directly detect it, which makes the processing of event streams often become pseudo-handling. Image frames, this approach loses the most innovative part of event cameras. At present, DAVIS, the best commercial event camera, still uses a combination of asynchronous and synchronous methods. Although there are other professional event cameras used in various fields, a more universal event-based algorithm framework has not yet been built. In the field of target recognition, the event camera has poor visibility and can only return the time, space, and polarity change information of the event. It cannot reflect the grayscale information or even the color information of the target. Although the current DAVIS can obtain grayscale information, it uses a combination of asynchronous and synchronous methods, which will be limited by the defects of traditional cameras. It is believed that after the development of an event-based algorithm framework, event cameras will develop more rapidly. In the field of target tracking, although the event camera has the characteristics of high dynamic range and low latency, the event generation rate will be greatly increased in the face of the scene where the camera and the scene change rapidly which will put pressure on data processing. Based on this situation, we should devote ourselves to the development of the framework of the algorithm directly based on the event, to give full play to the advantages of the event camera in future development.

In future development, in the fields of autonomous driving and aerospace, there is still little research on event cameras. In 2020, Afshar et al. applied event cameras to the aerospace field and proposed a feature-based detection and tracking method that can meet the needs of space situational awareness [50]. In the driving scene and the aerospace field, the target objects detected are large and have significant appearance characteristics. The influence of background noise can be ignored, and the scene changes at a high speed. In these fields, due to their good characteristics, event cameras may theoretically achieve better performance than standard cameras. In 2007, the Internet of Things gradually developed [51], and there are many related researches, such as node security [52-55], wireless sensor networks [56-59], data transmission between the cloud and mobile devices [60-62]. Due to their excellent characteristics, event cameras can also be developed in the field of IoT in the future. In IoT applications, event cameras can be connected to IoT domain names through a variety of wireless or wired communication networks. Due to its rapidity of reacting to scene information, it can better represent information.

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